Cost function Vs (oss function.

when we calculate $J(\beta_0, \beta_1)$ for each individual datapoints separately it's called

cost function Vs when we calculate $J(\beta_0, \beta_1)$ for all n datapoints at once

it's lass function.

[Iast Junction:
$$\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$$

$$J(\beta_0,\beta_1) = \frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$$

Loss function:
$$(y_i - \hat{y}_i)^2$$

$$J(\beta_0, \beta_1)$$

y: : Actual value of variable

y: : Predicted value of variable

n: Jatal no s of datapaints.

$$\beta_{i} = \beta_{i} - \alpha \left[\frac{\partial}{\partial \beta_{i}} (J(\beta_{i})) \right]$$

$$J(\beta_i) = J(\beta_o, \beta_1)$$

$$J(\beta_0,\beta_1) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^{t}$$

$$= \frac{1}{n} \sum_{i=1}^{n} (y_i - (\beta_0 + \beta_1 x_i))^2$$

For J = 0, above equation become:

$$J(\beta_o) = \frac{1}{n} \sum_{i=1}^{n} (y_i - (\beta_o + \beta_i x_i))^2$$

$$J(\beta_1) = \frac{1}{n} \sum_{i=1}^{n} (y_i - (\beta_0 + \beta_i, n_0))^2$$

Now finding the derevative using convergence algarithm.

$$\frac{\partial}{\partial \beta_i} J(\beta_i)$$

$$= \frac{\partial}{\partial \beta_{\circ}} J(\beta_{\circ})$$

$$= \frac{\partial}{\partial \beta_{0}} \frac{1}{n} \sum_{i=1}^{n} (y_{i} - (\beta_{0} + \beta_{i} \times i))^{2}$$

Case
$$II : J = 1 (J(\beta_1))$$

$$= \frac{\partial}{\partial \beta_i} J(\beta_i)$$

$$= \frac{\partial}{\partial \beta_{1}} \frac{1}{n} \sum_{i=1}^{n} (y_{i} - (\beta_{o} + \beta_{i} \times_{i}))^{2}$$

=
$$\frac{2}{n} \left[y_i - (\beta_0 + \beta_i x_i) \right] \times \chi_i$$

Combining above derevatives for J=0 and J=1 for the repeat Until Convergence.

$$\left\{\beta_{o} = \beta_{o} - \alpha \left[\frac{2}{n} \sum_{i=1}^{n} (y_{i} - (\beta_{o}(x)_{i}))\right]\right\}$$

$$\beta_{j} = \beta_{j} - \alpha \left[\frac{2}{n} \sum_{i=1}^{n} (y_{i} - \beta_{j}(x_{i})) \right] n_{i}$$

$$\beta(x_1) = \beta_0 + \beta_1 x_1$$